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Modeling the impact of climate change on water resources and soil erosion in a tropical catchment in Burkina Faso, West Africa

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ABSTRACT

Soil erosion is recognized as one main reason for soil degradation in West Africa. However, predictions on the impact of climate change on soil erosion are rare for most West African countries including Burkina Faso.

This study assesses the impact of climate change on water resources and soil erosion in a small catchment (126 km^2) in southwestern Burkina Faso. Climate data from an ensemble of six regional (RCM) and global (GCM) climate models were used to run the physically based spatially distributed hydrological and soil erosion model SHETRAN. The Representative Concentration Pathways (RCPs) 4.5 and 8.5 were selected as future climate scenarios.

Bias corrected precipitation and temperature required for the calculation of potential evapotranspiration were used as input for the SHETRAN model to simulate total discharge and specific suspended sediment yield (SSY). Discharge and SSY from simulations run with climate data were able to reproduce discharge and SSY from a simulation that used observed precipitation and temperature from the historical period (1971–2000).

The impact of climate change on hydrology and soil erosion was assessed by comparing the historical period with the future climate scenarios (2021–2050). Most of the used climate models predict an increase of temperature between 0.9 °C and 2.0 °C. The bias correction did not alter the climate change signal of temperature. Large uncertainties among the RCMs-GCMs exist regarding the climate change signal of future precipitation. Some climate models predict an increased (5.9%–36.5%) others a decreased (6.4%–10.9%) or mixed signal. The applied bias correction did not reverse the climate change signal in most cases but it influenced magnitude and timing of precipitation. The ensemble mean suggests an increased discharge between 19.5% (RCP 8.5) and 36.5% (RCP4.5) and an increased SSY of the same order. In general, the climate change signal and the corresponding discharge and SSY predictions are afflicted with large uncertainties. These uncertainties impede direct conclusions regarding future development of discharge and erosion. As a consequence of the mixed signals, potential increase and decrease of future discharge and soil erosion have to be incorporated in climate change adaption strategies.

1. Introduction

Hydrological and soil erosion processes are substantially driven by the atmosphere through rainfall and evapotranspiration. Rising temperatures are frequently predicted by regional (RCM) and global (GCM) climate models and are considered to change spatial and temporal rainfall pattern. Changing rainfall patterns and temperature have distinct effects on water resources and soil erosion (Field and Barros, 2014; Mullan et al., 2012; Nearing et al., 2004). The West African region is severely exposed to the effect of climate change due to the high vulnerability of the predominantly agricultural societies (Serdeczny et al., 2016). Analyzing the impact of climate change on hydrological and soil erosion processes is hampered by the lack of adequate data in terms of spatial and temporal resolution especially in a data scarce region as West Africa. Hydrological and soil erosion models are necessary to estimate past, present, and future development of water and soil resources. The modeled output can be used to provide guidance to decision makers regarding the implementation of climate change adaptation strategies (Beven, 2008; de Vente et al., 2013; Pandey et al., 2016). However, adaptation strategies necessary to mitigate the

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Table 1
Selected studies on the impact of climate change on water resources in West Africa (changed after Yira, 2016).

Study	Location/seize	GCM/RCM	Scenario	Reference period	Future period	Precipitation change (%)	Discharge change (%)	SSY change (%)
Hiepe (2008)	Upper Oueme/14,500 km^2	REMO-ECHAM5/MPI-OM	A1B, B1	1960–2000	2001–2050	− 3 to − 8	− 6 to − 23	− 5 to − 27
Itiveh and Bigg (2008)	Niger/1,471,000 km^2	HadCM3, PCM, CGCM, CSIRO	A1, A2, B1, B2	1950–2000	2070s	Mixed trend	− 15 to + 20	–
Kunstmann et al. (2008)	Volta Basin/94,000 km^2	ECHAM4	IS92a	1991–2000	2030–2039	− 20 to + 50	− 10 < to > + 20	–
Ardoin-Bardin et al. (2009)	Sassandra, Ivory Coast/62,173 km^2	HadCM3-A2	–	1971–1995	2036–2065	11.4	38	–
Kasei et al. (2010)	Volta Basin/400,000 km^2	MM5WRF and REMO-ECHAM5/MPI-OM	B1	1991–2000 and 1961–2000	2030–2039 and 2001–2050	+ 12 and − 6	+ 40 and − 5	–
Ruelland et al. (2012)	Bani catchment, Mali/100,000 km^2	MadCM3 and MPI-M	A2	1961–1990	2041–2070	− 2 to − 10	− 30 to − 46	–
Oguntunde and Abiodun (2013)	Niger/2.27 Mio km^2	RegCM3	A1B	1980–2000	2030–2050	− 13 to + 32.6	− 33 to + 35	–
Cornelissen et al. (2013)	Térou Catchment, Benin/2344 km^2	REMO-ECHAM5/MPI-OM	B1	2001–2010	2031–2049	− 11	− 11	–
Aich et al. (2014)	Niger Basin/2,156,000 km^2	HadGEM2-ES, IPSL-5 CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M, NorESM1-M	RCP8.5	1970–1999	2070–2099	Mixed trend	− 50 to + 50	–
Bossa et al. (2014)	Ouémé catchment, Benin/ 49,256 km^2	REMO-ECHAM5/MPI-OM	A1B	2000–2009	2010–2029	− 10	− 18	0
Mbaye et al. (2015)	Upper Senegal Basin, Senegal-Mali-Mauritania/218,000 km^2	REMO-MPI-ESM-LR	RCP4.5 and RCP8.5	1971–2000	2071–2100	Negative trend	Up to − 80	–

possible effects of climate change on hydrology, soil erosion and accordingly agriculture are challenging in the context of uncertain future climate change signals (Muerth et al., 2013).

The impact of climate change on the rainfall pattern and temperature in West Africa is difficult to assess due to differences between climate models regarding amplitude and direction of changing temperature and precipitation (Kasei et al., 2010; Niang et al., 2014). This is mainly attributed to the difficulties of simulating convective rainfalls and the rainfalls generated by the West African Monsoon (WAM) which is attributed to the incomplete knowledge of the involved processes, a lack of observations and the natural climate variability in the region (Cook, 2008; Druyan et al., 2010; Field and Barros, 2014; Klein et al., 2015; Niang et al., 2014). Consequently, climate model comparison studies report a large spread () of rainfall projections (Table 1). A trend towards the increase of frequency and magnitude of extreme precipitation events is debated and differs from region to region (Aguilar et al., 2009; Hounkpè et al., 2016; Mouhamed et al., 2013; New et al., 2006; Sylla et al., 2016b).

The effect of climate change on hydrology and soil erosion is difficult to assess using RCMs and GCMs due to their large uncertainty and biases regarding predicted rainfall patterns (Ehret et al., 2012; Hagemann et al., 2011; Muerth et al., 2013). Therefore, precipitation is frequently bias corrected to avoid unrealistic simulations and to enable correct impact assessment (Johnson and Sharma, 2015; Teutschbein and Seibert, 2012). Nevertheless, the application of bias correction is criticized because some assumptions of climate models are violated and the climate change signal may be changed (Ehret et al., 2012; Muerth et al., 2013). Because of this, a clear presentation and discussion of used data, differences between bias corrected and uncorrected results are necessary (Ehret et al., 2012). To account for the uncertainty in climate model predictions it is recommended to perform a multi-model assessment (Field and Barros, 2014). Therefore, in this study an ensemble of six RCMs-GCMs from the Coordinated Regional climate Downscaling Experiment project (CORDEX-Africa, http://www.cordex.org/) were used to evaluate the impact of climate change on hydrology and soil erosion in the Dano catchment.

Most of the available studies that used climate predictions for environmental models are focused on hydrological simulations. Studies that used climate change predictions of a multi-model ensemble as input to simulate the impact on hydrology and soil erosion are rare for the West African region (Li and Fang, 2016; Walling, 2009) but necessary as the effect of climate change on hydrology and soil erosion in this region is quite unclear (Niang et al., 2014). Mixed signals of discharge change are frequently reported by different studies in the region and may be attributed to the high uncertainty of precipitation projections for West Africa (Niang et al., 2014; Yira et al., 2017). A negative signal is reported to range from − 80% to − 11% (Table 1) for different climate models. Hiepe (2008) and Bossa et al. (2014) report negative signals for discharge in the Ouémé catchment in Benin as well as Ruelland et al. (2012) for the Bani catchment in Mali. Further negative discharge trends were found out by Mbaye et al. (2015) and Cornelissen et al. (2013). A positive trend is indicated by Ardoin-Bardin et al. (2009) for the discharge of the Sassandra catchment in Ivory Coast.

Among the listed studies only two deal with the impact of climate change on soil erosion. Both studies used the SWAT modeling system which is semi distributed and whose erosion module is based on the empirical MUSLE approach which does not consider gully and river bank erosion (Neitsch et al., 2011). Furthermore, the cited studies were conducted on a much larger scale ($\geq$ 2344 km^2).

Based on the described challenges, we aim to provide additional knowledge on the future impact of climate change on water and soil resources in West Africa with a focus on the Dano catchment in Burkina Faso. In this study we use the physically based spatially distributed hydrological and soil erosion model SHETRAN for the simulation of catchment discharge and soil erosion. SHETRAN was already tested in the Dano catchment (Op de Hipt et al., 2017) and was used to study the

climate change impact on hydrology and soil erosion in other regions (e.g. Bathurst, 2010; Birkinshaw et al., 2017; Zhang, 2015).

Based on the importance of knowledge on the future impact of climate change on water and soil resources for a society, which is highly dependent on rain-fed agriculture, the present study has the following objectives:

1) Compare bias corrected and uncorrected precipitation and temperature data of six climate models with measured data;
2) Analyze the climate change signal of temperature, mean and extreme precipitation;
3) Use observed and modeled historical precipitation and temperature as input to run SHETRAN and compare the corresponding simulated discharge and specific suspended sediment yield;
4) Assess the impact of climate change on discharge and specific suspended sediment yield by comparing the reference period (1971–2000) with the future period (2021–2050) and discuss the uncertainty related to the output of the different climate models.

2. Material and methods

2.1. Study area

The study catchment is located in the southern part of Burkina Faso, West Africa (Fig. 1a). The biggest settlement in the catchment is Dano after which it is named. The catchment covers an area of 126 km^2 and is one of three focal catchments of the West African Science Service Center on Climate Change and Adapted land use (WASCAL, www.wascal.org).

The catchment lies in the sudano savanna zone of West Africa whose natural vegetation is characterized by wooded and shrubby plant associations and abundant annual grasses. The natural vegetation has been extensively converted to cropland and settlement as shown by Yira et al. (2016) for the Dano catchment and by CILSS (2016) on the national level. The cropland is used to produce food crops such as sorghum (*Sorghum bicolor*), millet (*Pennisetum glaucum*), maize (*Zea mays*), cowpeas (*Vigna unguiculata*) and groundnut (*Arachidis hypogaea*). The most important cash crop in the area is cotton (*Gossypium hirsutum*).

Large parts of the study catchment are characterized by a flat topography with gentle slope gradients (average and maximum gradients are 1.8° and 20°, respectively). The flat landscape is interrupted by the Ioba mountain chain that covers the western part of the catchment (Fig. 1b). The elevation ranges from 269 m to 504 m above sea level.

The annual rainfall ranged from 800 to 1200 mm for the period 1951–2005 (Schmengler, 2010). The rainfall pattern is characterized by a distinct seasonality through the West African monsoon. The rainy season starts in July and ends in September. 65% of the mean annual precipitation falls in these months. The dry season ranges from October to June.

Soils are dominated by plinthosols (73%) which are characterized by high content of coarse particles and a plinthic subsurface layer. Soils of the valley bottoms are mainly gleysols. Other soils formed in the region are cambisols, lixisols, leptosols and stagnosols (Fig. 1e).

2.2. Climate data

Daily precipitation and mean daily temperature were available from a station operated by the national meteorological service (Direction Générale de la Météorologie du Burkina, DGM) for the period from 1971 to 2000 (see Fig. 1c).

Historical precipitation and temperature data for the same period (1971–2000) were retrieved from an ensemble of six RCM-GCMs (see Table 2). The RCM-GCM simulations were run in the framework of the Coordinated Regional climate Downscaling Experiment (CORDEX-Africa, www.cordex.org). The three RCMs (CCLM4-8: Climate Limited-area Modelling Community, Germany; HIRHAM5: Alfred Wegener Institute, Germany; RACMO22: Royal Netherlands Meteorological Institute, Netherlands) use the atmospheric boundary condition of four GCMs (CNRM-CM5: National Centre for Meteorological Research, France; EC-EARTH: consortium of 27 European members; ESM-LR: Max-Planck-Institute for Meteorology, Germany; NorESM1-M: Research Council of Norway, Norway).

Future temperature and precipitation projections for the period 2021–2050 were retrieved from the same RCM-GCM combinations. The Representative Concentration Pathways RCP 4.5 and RCP 8.5 (Moss et al., 2010) were used as future scenarios.

Datasets of the extent of 3 × 3 nodes with a distance of about 50 km surrounding the catchment were compared to investigate the rainfall variability in the region. However, due to the run time of SHETRAN and the small differences between the nodes as revealed in Section 3.1.1, the closest node was used only (see Fig. 1c) although different studies recommend the use of more nodes to account for climate variability (e.g. Villani et al., 2014).

2.2.1. Bias correction of precipitation and temperature data

Historical precipitation and temperature data from six climate models were compared with their observed counterparts for the period 1971–2000 to control if the modeled output is in agreement with the observation. The modeled temperature shows a negative deviation for most models (see Section 3.1.1). As temperature is used to calculate potential evapotranspiration and has therefore strong effects on catchment hydrology, it was bias corrected using the delta change approach described in Haddeland et al. (2012).

A bias correction method was used to correct the historical and future rainfall data derived from the six climate models. The non-parametric quantile mapping approach introduced by Gudmundsson et al. (2012) was applied. This approach derives monthly transfer functions from cumulative distribution functions of observed and modeled historical precipitation data and applies this transfer function to past and future modeled precipitation. Further details are given in Boé et al. (2007).

2.2.2. Analysis of extreme rainfall events

The determination of extreme values is done using the annual maxima series (AMS) method. AMS uses the annual precipitation maxima and is consequently limited to the number of years used for the study. Generalized Extreme Value (GEV) distributions were used to fit the empirical precipitation distributions. Monthly precipitation data of the reference period 1971–2000 were separated in two groups reflecting the characteristics of the seasons: Group 1 comprises the starting and the ending rainy season (April, May, October) and group 2 the rainy season (June, July, August, September). The GEV was fitted to the data of each group separately and the distribution parameters were estimated using the Generalized Maximum Likelihood Estimator (Gilleland and Katz, 2016). The fitted distribution was used to retrieve precipitation magnitude with return periods of 2-, 5-, 10-, 20-, 25- and 50-years for each group. In the following, precipitation magnitudes of each return period are called return levels. Bias corrected rainfall data from the projected scenarios (RCP 4.5 and RCP 8.5) of each RCM-GCM were analyzed based on the same approach. Finally, the percentage change D_i of the rainfall intensity (I_i) at the chosen return period (i) was calculated between the modeled historical data (A) and the future scenarios (B) by using equation Eq. (1) (Hounkpè et al., 2016):

$$D_i = \frac{(I_i(B) - I_i(A))}{I_i(B)} \quad (1)$$

where I_i (A) is the i-th intensity computed for the historical data and I_i (B) is the i-th intensity calculated for the future scenario data. The paired sample *t*-test and the Wilcoxon test were used to test for significant differences between the historical and future return levels. A change is considered as significant if both tests agree (Hounkpè et al., 2016).

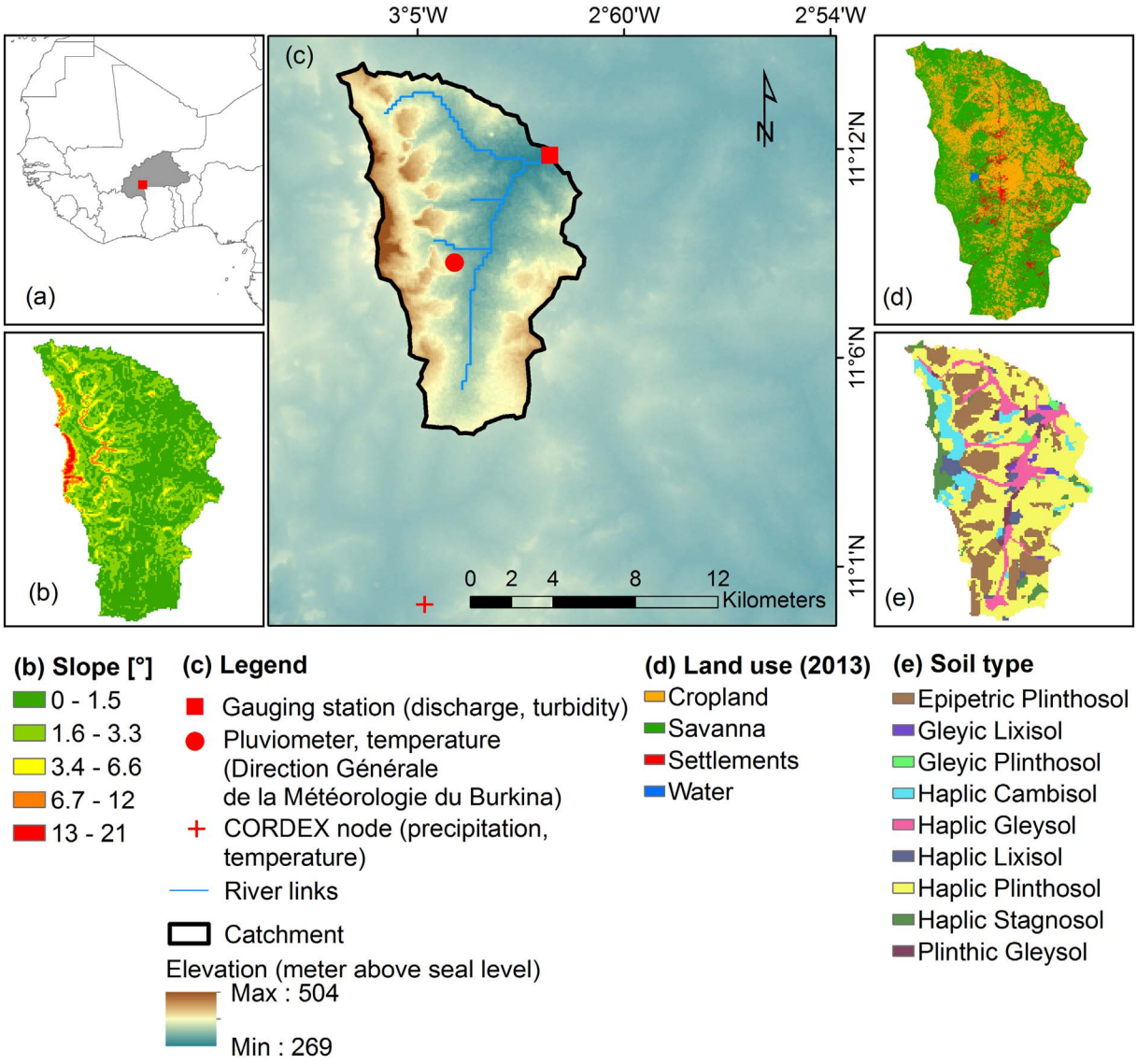

Fig. 1. Location map of the Dano catchment: (a) location of the catchment and Burkina Faso in West Africa, (b) slope of the catchment, (c) model catchment, (d) land use map (Forkuor, 2014), (e) soil map (data base: soil survey done by Ozias Hounkpatin, Institute of Crop Science and Resource Conservation, University Bonn).

Table 2
RCM-GCM products and labels.

Regional climate model	Driving global climate model	RCM centre/ institute	Labels
CCLM4-8	CNRM-CM5	CCLMcom	CCLM-CNRM
CCLM4-8	EC-EARTH	CCLMcom	CCLM-EARTH
CCLM4-8	ESM-LR	CCLMcom	CCLM-ESM
HIRHAM5	NorESM1-M	DMI	HIRHAM-NorESM
HIRHAM5	EC-EARTH	DMI	HIRHAM-EARTH
RACMO22	EC-EARTH	KNMI	RACMO-EARTH

2.3. Hydrological and soil erosion modeling

Observed and modeled precipitation and temperature data were used as climate input into the hydrological and soil erosion model SHETRAN (Birkinshaw, 2010; Ewen et al., 2000). SHETRAN is a physically based spatially distributed hydrological soil erosion model. It is a derivative of SHE (Système Hydrologique Européen), which was jointly developed by the British Institute of Hydrology, the Danish Hydraulic Institute and the French consulting company SOGREAH (Abbott et al., 1986). SHETRAN has been refined and complemented by new components as e.g. the fully 3D simulation of subsurface water flow (Parkin, 1996) and sediment transport (Wicks, 1988; Wicks and Bathurst, 1996). Detailed information is available online (http://research.ncl.ac.uk/shetran/). The model was already calibrated and validated in the Dano catchment. Detailed information on the parameterization can be found in Op de Hipt et al. (2017). The model was set up based on a 200 m × 200 m horizontal resolution and by using climate, discharge and suspended sediment load (SSL) data from the years 2013 and 2014 for calibration and validation respectively. Different performance measures (Nash Sutcliffe Efficiency (Nash and Sutcliffe, 1970), Kling-Gupta efficiency (Gupta et al., 2009; Kling et al., 2012) and R^2) for discharge are in the range of 0.7 and 0.79 for calibration and between 0.66 and 0.76 for validation. These measures are in the range of other studies that used SHETRAN (e.g. Birkinshaw et al., 2014; Đukić and Radić, 2014, 2016; Mourato et al., 2015; Naseela et al., 2015; Tripkovic, 2014; Zhang, 2015). Among these studies R^2 and NSE values above 0.5 are frequently observed. The calibration and validation of the erosion component showed NSE of 0.4 and 0.2 and R^2 of 0.47 and 0.37 for calibration and validation of SSL, respectively. These performance measures are in agreement with results of other studies (de Figueiredo

and Bathurst, 2007; Elliott et al., 2011; Zhang, 2015) and comparable with other erosion models (de Vente et al., 2013; Jetten et al., 1999). The calibrated model was used in the present work.

As hydrological and soil erosion data do not exist for the reference period the expected climate change impact on hydrology and soil erosion is estimated by studying the differences between the simulated hydrological and soil erosion variables of the reference period (1971–2000) and the future period (2021–2050).

The present study differentiates between suspended sediment load (SSL in kg/s) and suspended specific sediment yield (SSY in t/ha/year).

2.4. Time step sensitivity

The long term historical and future climate data was only available on a daily basis. This is critical since results of dynamic models such as SHETRAN respond sensitively to the chosen simulation time step (Bruneau et al., 1995; Hessel, 2005; Yira, 2016; Zhang, 2015) and consequently the discussion of time and spatial scales is fundamental in hydrological modeling (Blöschl and Sivapalan, 1995). Yira (2016) reports a decreasing modeled discharge with longer time step. This can be explained by the information loss during aggregation of rainfall data from sub-daily to daily resolution: It reduces the maximum precipitation intensities and therefore leads to an underestimation of overland flow due to infiltration excess. This effect is especially pronounced if the precipitation originates from convective storms which play an important role in the region. Consequently, simulated discharge and hence sediment yield may be underestimated by the model. In order to discuss the differences between hourly and daily simulations, observed hourly data were aggregated to daily data. Both data sets were used for the time step comparison. Fig. 2a shows that exceedance probabilities for both hourly and daily suspended sediment loads are rather small. Fig. 2b shows that there exists a statistically significant positive relation between hourly and daily suspended sediment loads. Interestingly, highest differences occur at both extremes of the data. The Wilcoxon signed rank test was applied to prove that the hourly and daily values are identical populations (H0: hourly and daily suspended sediment loads come from an identical population). To satisfy the assumption of the test that the paired values observations are randomly and independently drawn it was applied to a random set of paired values (Hogg et al., 2015). The test indicated that hourly and daily suspended sediment loads have similar populations (p-value = 0.2467). The limitations related to a daily timestep cannot be avoided for the long-term simulations as no hourly data are available. Furthermore, our results are comparable to other SHETRAN studies that also used a daily timestep (Birkinshaw et al., 2017; de Figueiredo and Bathurst, 2007; Mourato et al., 2015).

2.5. Assessment criteria

Different performance measures were used to investigate the RCM-GCM driven historical simulations and to compare observed and modeled climate data.

i. P-factor: It measures the proportion of observed climate data that is covered by the range of RCM-GCM derived climate data.
ii. R-factor: It expresses ratio between the range of minimum and maximum RCM-GCM for precipitation and temperature and the standard deviation of observed counterparts. Consequently, the R-factor indicates how wide the range of the modeled variable is, compared to the observed standard deviation:

$$R - \text{factor (Var)} = \frac{1}{n\sigma_{Var_{obs}}} \sum_{l=1}^{n} (Var_{Si_{max}} - Var_{Si_{min}}) \quad (2)$$

where Var is the climate variable, n the observation data points, Si_{min} and Si_{max} the minimum and maximum value of the RCM-GCM ensemble and σ the standard deviation.

iii. The normalized root mean square deviation (NRMSD), NSE (Nash and Sutcliffe, 1970), KGE (Gupta et al., 2009; Kling et al., 2012) and R^2 assess if the RCM-GCM based discharge and SSY simulations agree with the simulations run based on observed climate data.

3. Results and discussion

3.1. Climate data

3.1.1. Bias correction

The output of climate models necessary for hydrological and soil erosion modeling is frequently biased over the scale it is needed (Haddeland et al., 2012; Hagemann et al., 2011; Maraun et al., 2010; Randall et al., 2007). Therefore, the use of bias correction methods is frequently considered as inevitable although it is also debatable (Ehret et al., 2012). The lack of a physical justification and the possible violation of climate model assumptions by bias correction are criticized. Furthermore, bias correction may have a large influence on the climate change signal in terms of magnitude (Ehret et al., 2012). However, these disadvantages are often neglected due to the advantages of bias correction. The assessment of climate change impact on hydrology and hydrologically driven processes such as soil erosion is only useful for environmental planning, if the input data (especially precipitation) are realistic in term of magnitude and distribution (Muerth et al., 2013; Piani et al., 2010; Sharma et al., 2007; Teutschbein and Seibert, 2012).

The ability of uncorrected precipitation and temperature from the

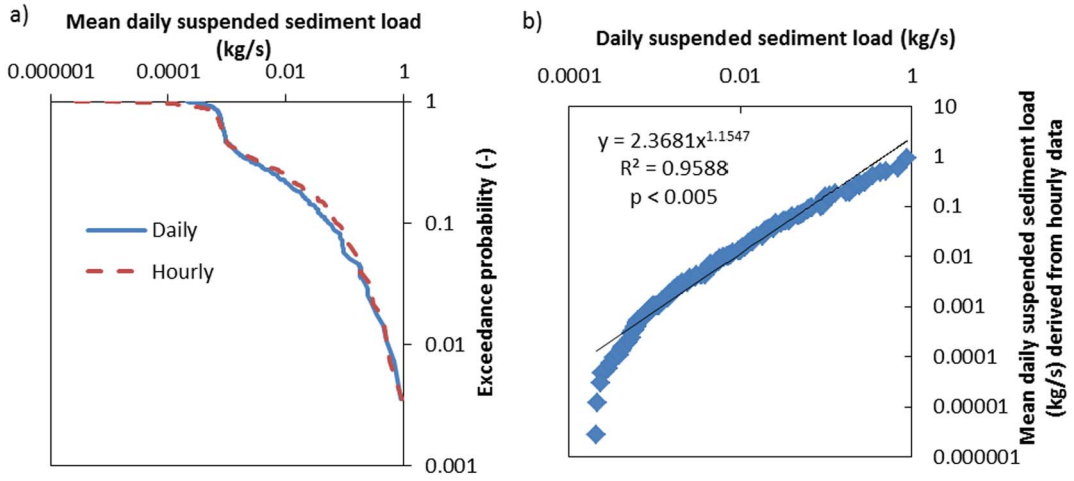

Fig. 2. a) Exceedance probability of hourly and daily suspended sediment load, b) scatter plot of hourly and daily suspended sediment load. LOG10 scale is used.

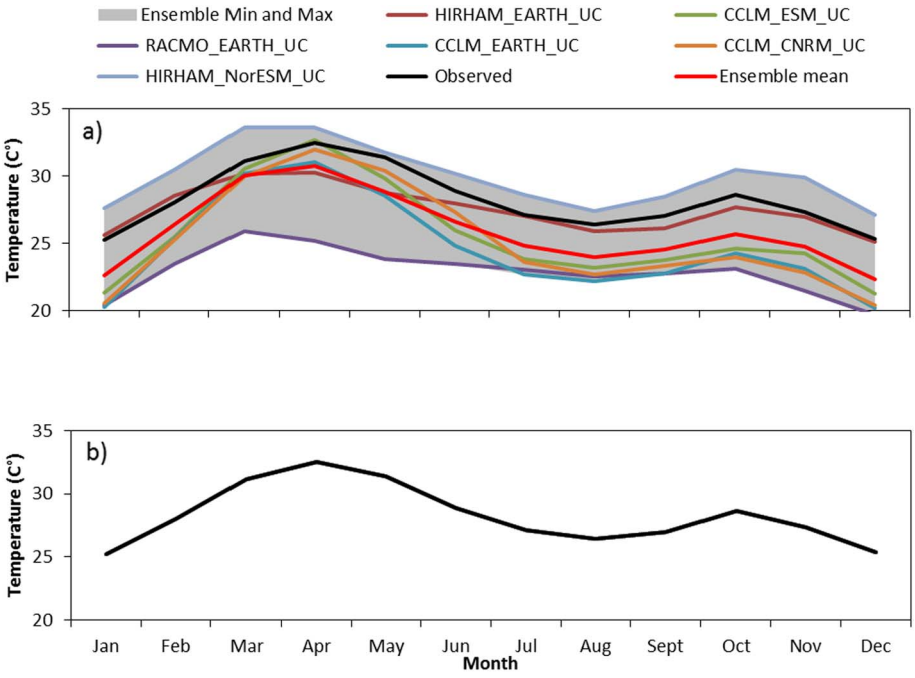

Fig. 3. Observed, uncorrected (a) and bias corrected (b) mean monthly temperature data for the reference period 1971–2000. Due to the small differences data from climate models are graphically masked by the observed temperature.

RCM-GCM ensemble to reflect observed data is expressed by the coefficient of determination and the normalized root mean square deviation (NRMSD). All climate models clearly differ from the observed data. The observed temperature is better represented by the modeled data as shown by correlation coefficients between 0.57 and 0.78 compared to precipitation with values between 0.4 and 0.68. The best correlation coefficients are achieved by HIRHAM-EARTH for precipitation (0.68) and temperature (0.78). Especially precipitation data show a high deviation with NRMSD values of higher than 0.73. The deviation of temperature is smaller with a minimum NRMSD of 0.2 (CCLM-ESM).

Fig. 3a shows that the observed mean monthly temperature is within the temperature range as simulated by the ensemble of climate models. However, mean monthly observed temperature is frequently higher than temperature derived from the climate models. Temperature is used to calculate potential evapotranspiration (ETP) using the Hamon equation (Oudin et al., 2005). Therefore, temperature indirectly influences discharge and soil erosion by controlling ETP (Chaplot, 2007; Li and Fang, 2016). To avoid inconsistencies between observed and modeled potential evapotranspiration, temperature was bias corrected. The bias correction led to an overall agreement between observed and modeled temperature as shown in Fig. 3b. Due to the small differences data from climate models are masked by the observed temperature.

The question of how many nodes to include in climate change studies to account for the spatial climatic variability is frequently discussed (e.g. Villani et al., 2014). Yira et al. (2017) for example used 9 nodes for a larger catchment of the same river system and did the hydrological modeling for each of these nodes. We compared uncorrected and bias corrected rainfall data of each climate model from a rectangular grid of 3 × 3 nodes surrounding the catchment. Fig. 4 shows the exceedance probability of the modeled rainfall from 9 nodes from HIRHAM-EARTH and the observed rainfall data. The inter-node deviation and the deviation between the uncorrected data and the observed are quite large as shown in Fig. 4a and c. After the bias correction (Fig. 4b and d) the deviation between modeled and observed as well as the inter-node deviation is negligible. A similar pattern was also observed for the remaining five climate models (data not shown). Based on the small difference between the nodes data from the closest node were used only.

Fig. 5a shows that uncorrected precipitation of most RCMs-GCMs overestimate magnitude of mean monthly precipitation compared to the observed rainfall. Furthermore, the timing of the rainy season partly disagrees with the observed pattern. The differences between mean monthly precipitation from all climate models and the observed precipitation are considerably reduced after bias correction (Fig. 5b). Bias corrected mean monthly precipitation reflects well timing and magnitude of the rainy season. Fig. 5c shows that annual precipitation is frequently overestimated by uncorrected data from all climate models. Despite the large spread (R-factor = 4.8) only 60% of observed rainfall falls within the modeled precipitation range. As result of the applied bias correction (Fig. 5c) the P-factor increases (P-factor = 86%) while the R-factor decreases (R-factor = 3.6). The modeled precipitation range agrees with the observed precipitation quite well but observed data are slightly lower than modeled precipitation.

The ability of the six selected RCMs-GCMs to reproduce the West African climate has already been proven in previous studies (Cook and Vizy, 2006; Dosio et al., 2015; Gbobaniyi et al., 2014; Paeth et al., 2011; Yira et al., 2017). Furthermore, as already shown by Yira et al. (2017), the selected RCM-GCM give a quite large range of the possible impact of climate change on hydrology in this region. The overestimation and misrepresentation of the timing of the rainy season, that rectifies the bias correction of precipitation, is also reported by other authors for sub-Saharan Africa (Nikulin et al., 2012; N'Tcha M'Po et al., 2016; Oyerinde et al., 2017; Paeth et al., 2011).

3.1.2. Climate change signal

A comparison of the uncorrected and bias corrected historical temperature with the future temperature shows a clear increase for most climate models and scenarios. An exception is RCP4.5 of HIRHAM-EARTH which projects a decrease in temperature (Table 3). The bias corrected ensembles show a mean increase of 3.4% (RCP4.5) and 5.4% (RCP8.5), which is slightly lower than the uncorrected temperature increase. The bias correction did not change the climate signal of the uncorrected data. Increasing temperatures over West Africa were already observed for the last 50 years and different studies suggest that this trend will continue in the future (Niang et al., 2014; Waongo, 2015). Rising temperatures are observed by all multi-model ensemble studies conducted in the region (Field and Barros, 2014).

Table 4 shows the relative change of predicted precipitation (2021–2050) from all climate models and scenarios compared to the historical period (1971–2000). It is important to notice that the climate

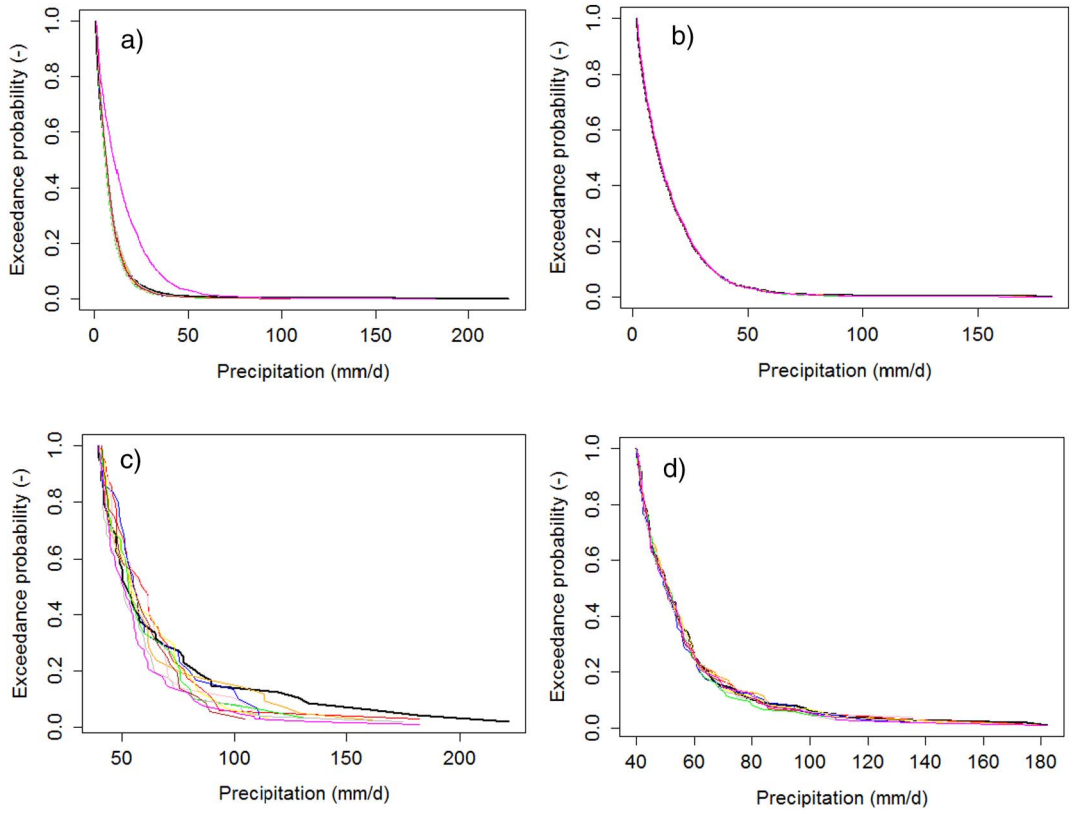

Fig. 4. (a) Exceedance probability of uncorrected modeled rainfall data and the observed rainfall data (magenta line) from each node (9) for the reference period 1971–2000, (b) exceedance probability of bias corrected modeled rainfall data and the observed rainfall data from each node (9), (c) exceedance probability of uncorrected modeled rainfall data and the observed rainfall data from each node (9) with a threshold of > 40 mm/d, (d) exceedance probability of bias corrected modeled rainfall data and the observed rainfall data from each node (9) with a threshold of > 40 mm/d. All data are from HIRHAM-EARTH.

models do not agree on one common signal. Increased precipitation (5.9%–36.5%) is predicted by RCP4.5 of HIRHAM-EARTH and by RACMO-EARTH, CCLM-CNRM and HIRHAM-NorESM while a decrease (0.2%–10.9%) is projected by RCP8.5 of HIRHAM-EARTH and by CCLM-ESM and CCLM-EARTH. HIRHAM-EARTH is characterized by a mixed precipitation signal. The disagreeing signals between models may be attributed to data scarcity and limited knowledge of the regional climatology (Niang et al., 2014). The Coupled Model Intercomparison Project Phase 5 (CMIP5) showed different precipitation changes till 2050 (Field and Barros, 2014).

The trend suggested by the uncorrected data seems to be maintained after bias correction. The only exception is RCP4.5 of CCLM-ESM whose signal is changed from 0.01% to − 4.2%. This can be explained by the bias correction method. If the difference between historical and uncorrected precipitation is very small, bias correction may lead to an inversion of the signal. As Hagemann et al. (2011) points out, “the impact of bias correction on the climate change signal may be larger than the signal itself” (Hagemann et al., 2011, p. 575) if the signal is small.

Fig. 6 shows the mean relative change of bias corrected precipitation return levels of six return periods for each model and RCP. For RCP4.5 (Fig. 6a) it is observable that return levels of most models (HIRHAM-EARTH, RACMO-EARTH, CCLM-CNRM, HIRHAM-NorESM) are predicted to increase. For example, the 50-year return level of RCP4.5 of HIRHAM-EARTH is predicted to increase by 193%. In agreement with the overall negative precipitation signal of CCLM-EARTH (see Table 4), return levels of this model decrease over all return periods. For RCP8.5 all models except CCLM-ESM are characterized by increased return levels (0.4%–226.8%). The change in return levels for bias corrected data from most models and RCPs is statistically significant as tested by the paired *t*-test and the Wilcoxon test. A similar trend also applies to the data from April, May and October (not shown here). RCP4.5 of HIRHAM-EARTH and both RCPs of HIRHAM-NorESM show larger increases in return levels. This is attributed to very high precipitation extremes of > 500 mm/d which remain improbable even after bias correction. However, the inclusion of extremely high precipitation rates may substantially influence the fitted extreme value distribution and the predicted return levels accordingly.

The change in magnitude and frequency of extreme precipitation due to climate change is frequently attributed to the increase of atmospheric moisture content (Emori and Brown, 2005; O'Gorman and Schneider, 2009). Global studies report mixed signals depending among other on the chosen climate model and the scenario (Field et al., 2012; Field and Barros, 2014). Studies that focused on the investigation of climate change impact on extreme precipitation are rare in the West African region. Some of the available studies work with historical precipitation (Aguilar et al., 2009; New et al., 2006; Hounkpè et al., 2016) and do not use future scenarios from climate models. Sylla et al. (2016b) compared different climate models available in the CORDEX framework and report a precipitation change between − 10% and + 10% with greater amplitudes. They further notice an increase of very wet days between + 5% and + 10%. Druyan (2011) reviews several studies on precipitation trends and reports a mixed signal. Other studies that used climate model derived precipitation data consistently report increased magnitude of high intensity precipitation events for the West African Region. (Abiodun et al., 2013; Giorgi et al., 2014; Lintner et al., 2012; Scoccimarro et al., 2013; Vizy and Cook, 2012).

3.2. Modeling

3.2.1. Hydrology

3.2.1.1. Historical simulated discharge. SHETRAN was run with

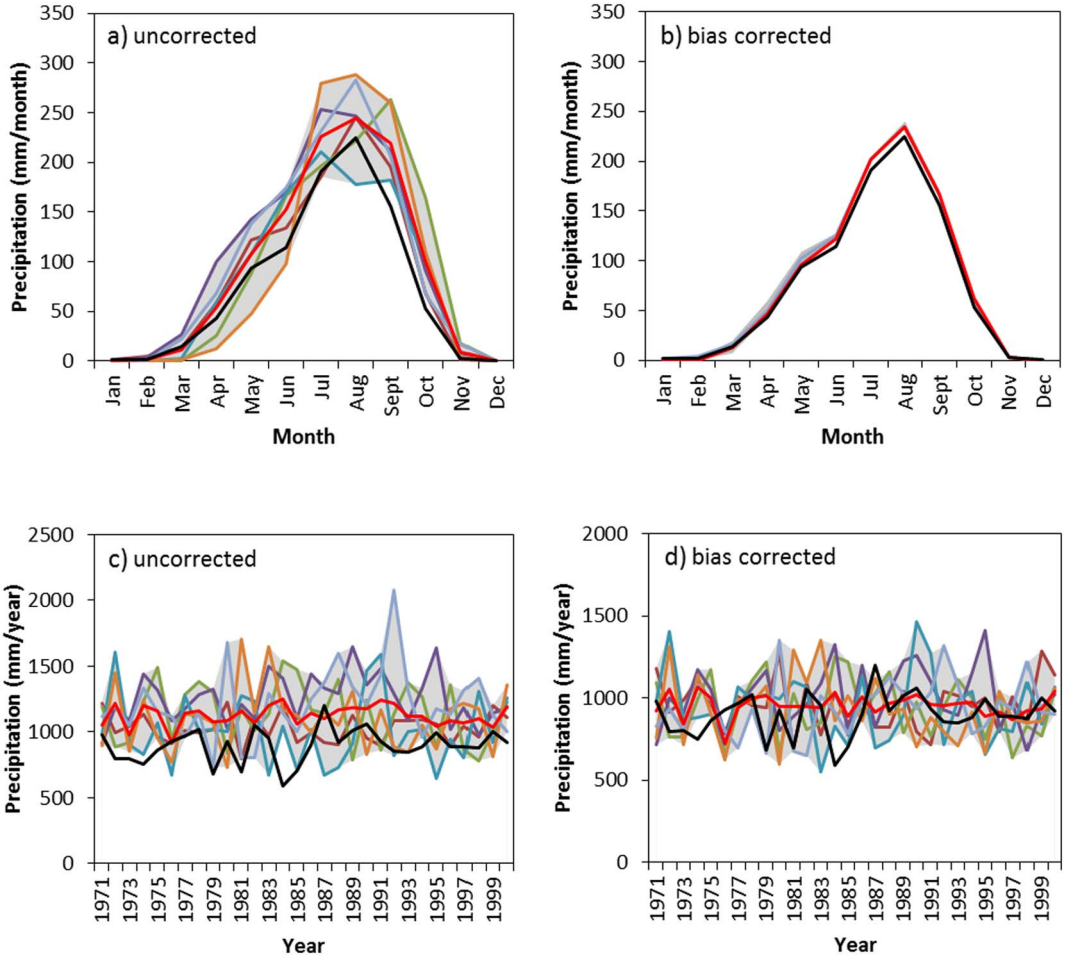

Fig. 5. Historical mean monthly (a, b) and mean annual (c, d) precipitation for the reference period 1971–2000.

observed and modeled climate data. The discharge and SSY simulated using observed climate variables is denoted as observed discharge/SSY and the discharge and SSY simulated using modeled climate data is indicated by modeled discharge/SSY. If not differently indicated, all data retrieved from climate models are bias corrected.

To test the ability of modeled discharge to reproduce the observed discharge, modeled mean monthly discharge was compared to observed mean monthly discharge over the reference period (1971–2000). Fig. 7 shows that modeled discharges are mostly overestimated compared to observed discharge. The use of uncorrected precipitation data from CCLM-ESM additionally leads to a shift of the peak discharge to September.

Performance measures (NSE, R^2, KGE) are used to quantify the ability of the RCMs-GCMs to reproduce the historical discharge simulated based on measured precipitation and temperature. Table 5 shows that all climate models reproduce timing and magnitude of discharge well. Differences between observed and modeled discharges may be explained by varying temporal patterns of precipitation and potential evapotranspiration. Precipitation of RACMO-EARTH, for example, is frequently higher than observed precipitation despite bias correction. The use of uncorrected precipitation and temperature data (CCLM-ESM-UC) leads to an overestimation and wrong timing of the discharge. Yira et al. (2017) used the same data base and also state a trend towards discharge overestimation by most models. They argue that shortcomings regarding the bias correction approach, which was run using a monthly correction, may be responsible for the overestimation of precipitation and consequently also for the simulated discharge.

3.2.1.2. Future simulated discharge change. The impact of climate change on discharge is assessed by comparing the historical discharge

Table 3
Relative temperature change of RCP4.5 and RCP8.5 (2021–2050) compared to the reference period (1971–2000).

RCM-GCM	Uncorrected			Bias corrected		
	Mean historical temperature (°C)	Temperature change RCP 4.5 (%)	Temperature change RCP 8.5 (%)	Historical temperature (mm)	Temperature change RCP 4.5 (%)	Temperature change RCP 8.5 (%)
HIRHAM_EARTH	27.5	− 2.8	5.6	28.2	− 2.7	5.5
CCLM_ESM	25.5	6.6	7.7	28.2	5.9	6.9
RACMO_EARTH	22.9	6.2	6.5	28.2	5.0	5.3
CCLM_EARTH	24.6	6.0	6.8	28.2	5.3	5.9
CCLM_CNRM	25.2	4.0	5.3	28.2	3.6	4.7
HIRHAM_NorESM	29.9	3.2	3.6	28.2	3.3	3.8
Ensemble mean	25.9	3.9	5.9	28.2	3.4	5.4

Table 4
Relative change of mean annual precipitation between reference period (1971–2000) and future period (2021–2050). Uncorrected and bias corrected mean values are used for calculation. Bias correction was performed using observed data with mean annual precipitation of 897 mm.

RCM-GCM	Uncorrected			Bias corrected		
	Mean historical precipitation (mm)	Precipitation change RCP 4.5 (%)	Precipitation change RCP 8.5 (%)	Historical precipitation (mm)	Precipitation change RCP 4.5 (%)	Precipitation change RCP 8.5 (%)
HIRHAM-EARTH	1029.6	23.7	− 1.8	961.7	36.5	− 0.2
CCLM-ESM	1143.9	0.01	− 7.0	942.2	− 4.2	− 6.4
RACMO-EARTH	1253.4	7.2	16.1	1005.2	9.0	18.1
CCLM-EARTH	1014.7	− 14.1	− 8.1	944.2	− 10.9	− 6.4
CCLM-CNRM	1099.0	16.2	25.7	929.9	10.8	19.3
HIRHAM-NorESM	1209.1	4.5	17.1	941.2	5.9	12.0
Ensemble mean	1125.0	6.3	7.0	954.1	7.8	6.1

as simulated using precipitation and temperature from climate models to the future discharge (both simulated using data from climate model scenarios). Table 6 shows that only HIRHAM-EARTH shows different signals for RCP4.5 and RCP8.5 with a strong increase in discharge for RCP4.5 and decrease for RCP8.5. Three climate models (RACMO-EARTH, CCLM-CNRM, HIRHAM-NorESM) project an increase of discharge between 15.2% and 67.7% whereas two models (CCLM-ESM, CCLM-EARTH) indicate a decrease between 21.8% and 42.9%. The precipitation signal is reflected by the discharge change across all models. The ensemble mean suggest an increase of discharge for both emission scenarios. High future discharge gains correspond to increasing return levels as observed in Section 3.1.2. For example, RCP4.5 of HIRHAM-EARTH shows a very large discharge increase and high positive changes of return levels whereas discharge and return levels of CCLM-EARTH are predicted to decrease (see Fig. 6). Table 1 gives an overview over selected studies that investigate the impact climate change on hydrology. The range of future discharge change reported by these studies roughly corresponds to the ranges presented in Table 6 with the exception of RCP4.5 of HIRHAM-EARTH.

In general, changes in discharge can be explained by the combination of the climate model predictions regarding precipitation, temperature and accordingly potential evapotranspiration. Increased temperature will amplify evapotranspiration, which results in decreased runoff assuming stable or decreasing precipitation while increased rainfall leads to increased discharge assuming temperature/evapotranspiration stagnates or is reduced. In addition to the direct effects through changed rainfall and temperature characteristics, feedbacks with soil and vegetation properties as well as land use change may have an even stronger impact on change in water discharge (Mullan et al., 2012; Slaymaker, 2001) but are not considered in the present study due to limited knowledge and model restrictions. The sensitivity of discharge simulated by SHETRAN to changes in precipitation and potential evapotranspiration (ETP) is shown in Fig. 8. The correlation between precipitation and simulated discharge (Fig. 8a) is positive while the relationship between ETP and discharge (Fig. 8b) is negative. Both relations are statistically significant. For RCP4.5 an increase of precipitation by 20% leads to an increase in discharge of 100% while an increase of ETP by 20% results in a negative discharge change of 161%. For RCP8.5 the same increase in precipitation would lead to an increase of discharge of 68% and an increase in ETP of 20% would result in a discharge change of − 156%. These numbers and the comparison of the regression slopes between precipitation and ETP

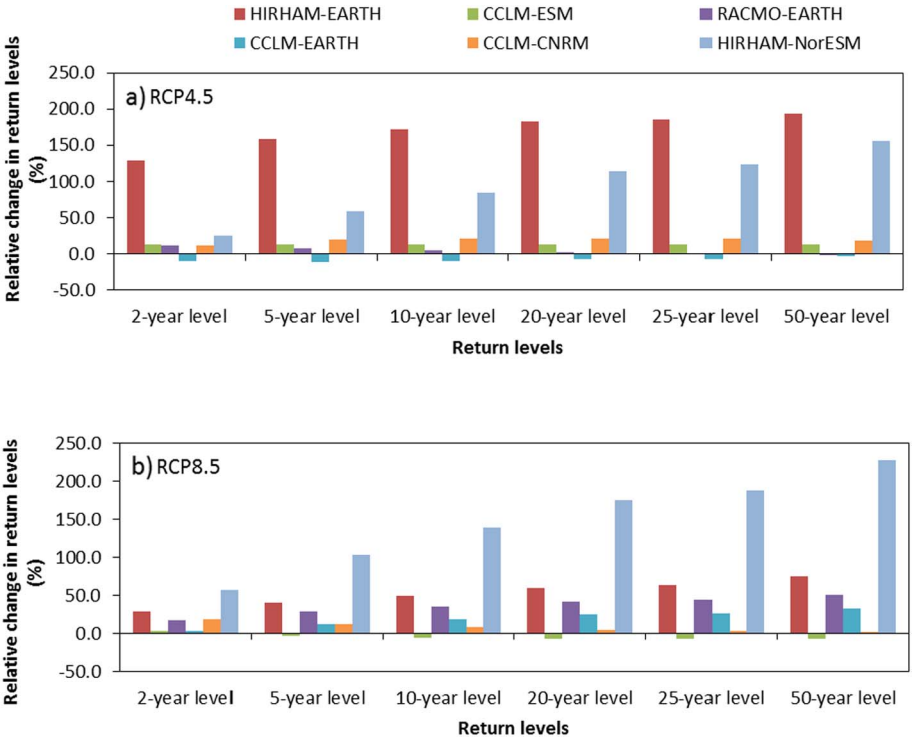

Fig. 6. Relative change (%) of rainfall return levels (2021–2050) for (a) RCP4.5 and (b) RCP8.5 compared to the reference period (1971–2000). The change was calculated based on the bias corrected data.

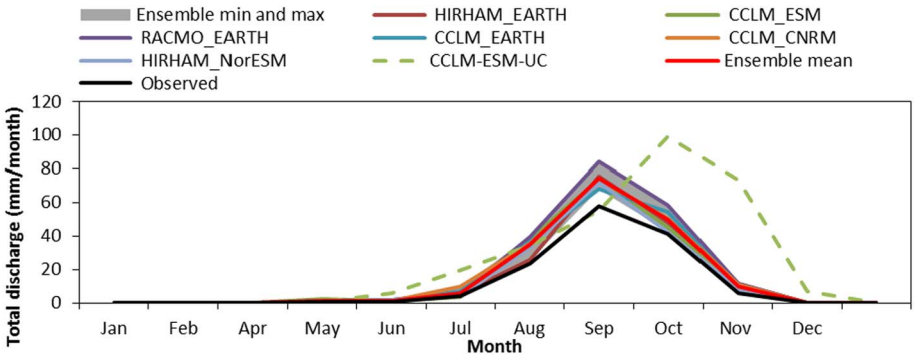

Fig. 7. Modeled discharge using observed and modeled precipitation for the reference period (1971–2000). CCLM-ESM-UC refers to the uncorrected data.

Table 5
Performance measures of discharge and SSY simulated based on climate models and observed precipitation. Calculation basis are mean monthly discharges/SSY for the reference period. NSE refers to the Nash-Sutcliffe-Efficiency, R^2 to the coefficient of determination and KGE to the Kling-Gupta-Efficiency.

Model	Discharge			Soil erosion		
RCM-GCM	NSE	R^2	KGE	NSE	R^2	KGE
HIRHAM-EARTH	0.91	0.99	0.74	0.84	0.97	0.73
CCLM-ESM	0.88	0.98	0.70	0.83	0.98	0.66
RACMO-EARTH	0.69	1.00	0.49	0.58	1.00	0.45
CCLM-EARTH	0.89	0.99	0.65	0.86	0.99	0.64
CCLM-CNRM	0.87	0.99	0.62	0.82	0.99	0.59
HIRHAM-NorESM	0.93	0.99	0.78	0.89	0.98	0.75
CCLM-ESM-UC	− 0.99	0.53	− 0.25	− 1.96	0.52	− 0.50

suggest that a changing ETP has a stronger impact on discharge then precipitation. This is not always the case as shown by Yira et al. (2017) who identified precipitation as major factor whereas ETP is reported to have no significant influence on discharge as the environmental system is water limited and not energy limited. Differences between the models (SHETRAN, WaSiM) and their parameterization may be responsible for the different results (Op de Hipt et al., 2017; Yira et al., 2016). A discussion of the uncertainties related to the calculation of temperature based ETP is given in Kingston et al. (2009).

The mixed discharge signals result from uncertain precipitation predictions for the West African region due to the described difficulties in modeling the West African climate (Field and Barros, 2014). As a consequence, this uncertainty will be propagated as these data are required input to environmental models. Fig. 9 shows the uncertainties of discharge simulations, which are attributed to the different climate model outputs. The large inter-annual and inter-model variability becomes evident and underlines the need to include several climate models in climate change studies in order to cover the range of possible developments (Sylla et al., 2016a; Zhang et al., 2011).

3.2.2. Soil erosion

3.2.2.1. Historical simulated soil erosion. The specific suspended sediment yield (SSY) simulated with observed precipitation and temperature data (observed SSY) is compared to the SSY simulations fed with bias corrected precipitation and temperature data of the six RCMs-GCMs (modeled SSY). Fig. 10 shows that all climate models lead to a higher modeled SSY compared to observed SSY. Since soil erosion is mainly driven by surface runoff, the described pattern is similar to what has been discussed before (see Section 3.2.1.1). The use of uncorrected precipitation data leads to an extreme overestimation and to a temporal shift of peak SSY and is not recommended to assess the future impact of climate changes on soil erosion.

Performance measures (NSE, R^2, KGE) are used to express the capability of climate models to provide input data for SSY models. Data of all models are able to reproduce magnitude and timing of SSY derived from observed precipitation. The performance values range from 0.4 to 1. Further details are given in Table 5.

3.2.2.2. Future simulated soil erosion. The impact of climate change on soil erosion is investigated by comparing the relative differences between climate model driven historical simulations (1971–2000) and the future scenarios (2021–2050). Table 6 shows that three models predict an increase (14.1%–64.4%) of soil erosion (RACMO-EARTH, CCLM-CNRM, HIRHAM-NorESM) while two models (CCLM-ESM, CCLM-EARTH) forecast a decreasing trend (21.2%–45%) of soil erosion. The RCPs of HIRHAM-EARTH give a mixed signal. The erosion predictions follow the same trend as the precipitation and discharge predictions. The signal based on uncorrected precipitation data (CCLM-ESM-UC) correspond to the bias corrected counterpart. The unclear climate change signal is also stated by Li and Fang (2016) who reviewed > 200 climate impact studies indicating increasing and decreasing future erosion trends. They underline that future uncertainty in erosion is above all a result from uncertainty in precipitation predictions.

The described change of future erosion rates can be explained by direct and indirect, positive and negative climatic impacts on soil erosion. Changing spatiotemporal patterns and magnitudes of precipitation

Table 6
Mean relative change of mean annual discharge/suspended sediment yield (SSY) as projected by the climate model ensemble for the future period (2021–2050) compared to the historical period (1971–2000). CCLM-ESM-UC refers to the uncorrected data. The mean annual discharge simulated using observed climate data is 133.6 mm.

RCM-GCM	Historical discharge (mm)	Discharge change RCP 4.5 (%)	Discharge change RCP 8.5 (%)	Historical SSY (t/ha/year)	SSY change RCP 4.5 (%)	SSY change RCP 8.5 (%)
HIRHAM-EARTH	167.8	207.5	− 5.8	0.0911	217.3	− 4.8
CCLM-ESM	173.8	− 21.8	− 24.7	0.0969	− 21.2	− 24.8
RACMO-EARTH	202.1	15.2	43.4	0.1121	14.1	44.4
CCLM-EARTH	178.9	− 42.9	− 27.4	0.0980	− 45.0	− 26.6
CCLM-CNRM	183.3	31.6	63.8	0.1014	30.4	64.4
HIRHAM-NorESM	162.6	29.4	67.7	0.0898	23.4	59.5
CCLM-ESM-UC	167.8	− 8.5	− 30.1	0.1760	− 7.1	− 29.6
Ensemble mean	173.8	36.5	19.5	0.1	36.5	18.7

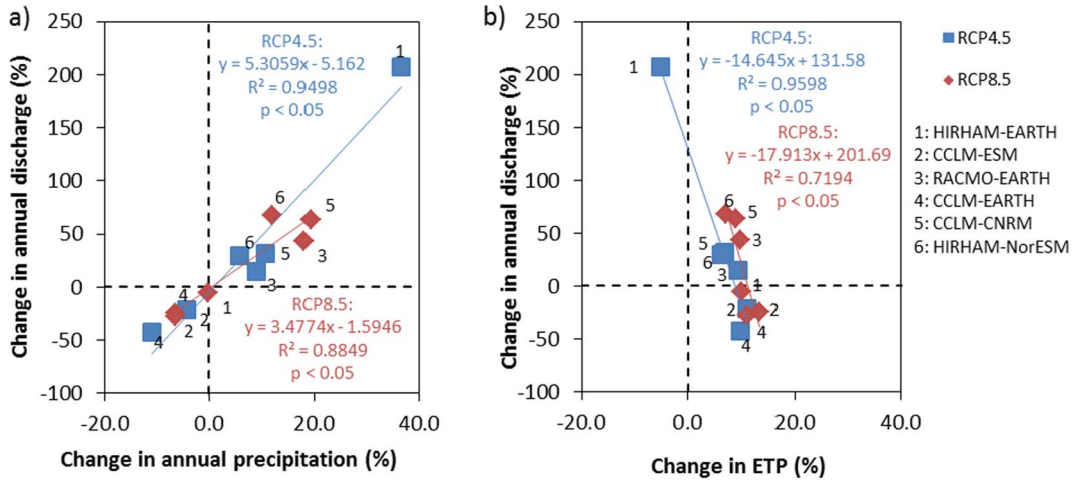

Fig. 8. Simulated future discharge change vs. bias corrected annual precipitation change (a) and potential evapotranspiration (ETP) change (b) under emission scenarios RCP4.5 and RCP8.5. Relative changes are calculated by comparing the reference period (1971–2000) with the future period (2021–2050).

are expected to directly influence hydrological processes like runoff (Fig. 8) and consequently soil erosion rates through altered conditions of soil/sediment entrainment and transport. Increased soil erosion rates are sometimes reported even if the precipitation sum is expected to decrease (Nunes et al., 2013). This can be explained by increased rainfall intensities as also predicted by some RCMs-GCMs for the present study catchment (see Fig. 6). Especially semi-arid environments, in which Hortonian runoff dominates, are susceptible to increased rainfall intensities. The importance of extreme precipitation events for annual specific suspended sediment yield is also reflected by our data. In average around 25% of the predicted annual SSY across all models originates from maximum daily SSY. The analyses of predicted return levels (see Section 3.1.2) and the comparison of historical with future monthly maximum precipitation (data not shown) show that the contrasting combination of decreasing precipitation sums and increasing erosion rates as a result of increasing precipitation intensities are not observed in this study.

Indirect impacts are expected from changing temperatures which may lead to altered vegetation zones, plant properties and changed vegetation phases. Agricultural adaption strategies like revised planting and harvesting dates and new crops may also lead to increase or decrease of soil erosion rates. However, the impact of climate change does not need to be negative as increased precipitation, temperature and CO_2 concentrations may increase plant biomass, vegetation canopy and the growing season (Li and Fang, 2016). As already stated above the relationships and complex feedback mechanisms between hydrology and consequently soil erosion and climate as well as land use change are very complex. A combined analysis of the impact of land use and climate change may lead to increased erosion rates as human induced land use change is expected to negatively affect discharge and accordingly soil erosion (Yira et al., 2016). Furthermore, cultivated soils are considered to be more susceptible to climate change than the uncultivated counterparts (Nunes et al., 2013). The indirect impacts like human or climate induced land use change may be even stronger than the direct effect of climate change (Latocha et al., 2016; Li and Fang, 2016).

Fig. 11 shows the mean monthly SSY of all climate models and scenarios. The distinct differences between models reflect the large uncertainties of future climate and erosion predictions. The largest erosion rates are predicted by RCP4.5 of HIRHAM-EARTH for the rainy season (Fig. 11a). A substantial amount of uncertainty is also added by RCP4.5 of HIRHAM-EARTH which predicts monthly erosion rates to be up to 5.7 times higher than the model mean. Except for HIRHAM-EARTH predicted erosion rates are similar for RCP8.5.

Predicted annual SSY (0.11 t/ha/year–0.13 t/ha/year for all models and RCPs) are considerably lower than current global erosion rates which are estimated to be 10.2 t/ha/year (Li and Fang, 2016). Schmengler (2010) investigates current soil erosion in the same area using the WATEM/SEDEM modeling approach and reports simulated SSY between 0.4 t/ha/year and 3.4 t/ha/year. It is worth to underline that SHETRAN was calibrated and validated using turbidity derived suspended sediment loads (SSL) as these data were available (Op de Hipt et al., 2017). Consequently, SSY of the suspended sediment fraction are lower than sums across all fractions. However, as the model was calibrated using SSL, only the suspended sediment fraction is considered. This explains why the simulated erosion rates are

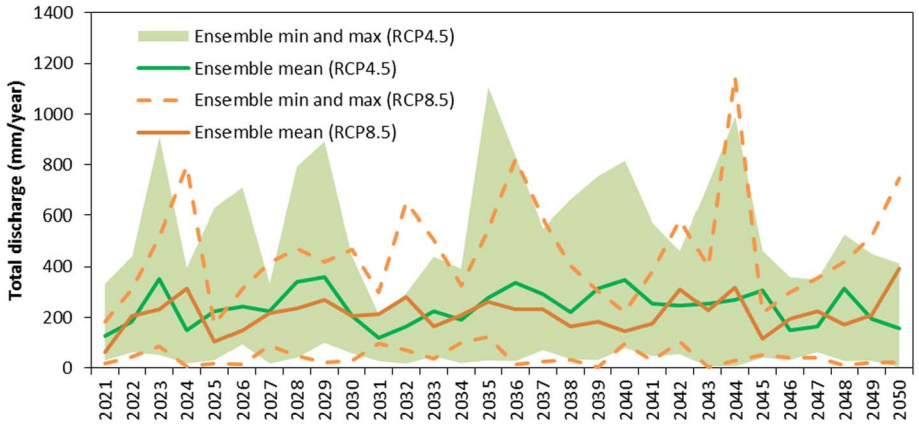

Fig. 9. Annual total simulated discharge as projected by bias corrected data from the climate model ensembles for RCP4.5 and RCP8.5.

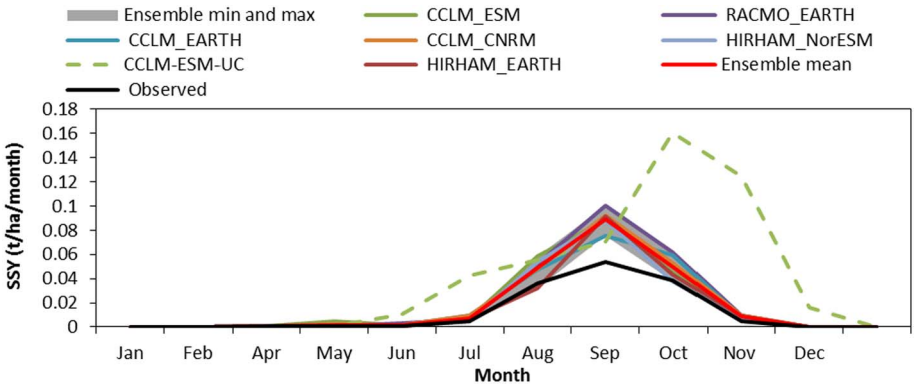

Fig. 10. Observed and modeled precipitation based specific suspended sediment yield (SSY) as simulated for the reference period (1971–2000). CCLM-ESM-UC refers to the uncorrected data.

substantially lower. Despite the high vulnerability of savannas to soil degradation caused by water erosion, the low erosion rates in the Dano catchment are also caused by the gentle hillslope gradients.

Comparable analyses of future impact of climate change on soil erosion are rare for West Africa in general and especially on a catchment scale as used in this study (Li and Fang, 2016; Walling, 2009). Yang et al. (2003) assessed the impact of future climate change on soil erosion on the global scale and reports an increase for the African continent. Studies conducted on a smaller scale suggest a mixed signal ranging from a decrease in soil erosion by 5% to 27% (Hiepe, 2008) to no change (Bossa et al., 2014) (see Table 1). However, given the small number of studies, different climate models, different spatial scales, varying environmental conditions and modeling approaches a direct comparison between the studies is challenging.

4. Conclusion

The present study assessed the impact of climate change on hydrological and soil erosion processes by the mid-21st century by using data from the CORDEX-Africa project to feed the hydrological and soil erosion model SHETRAN.

1) We showed by the comparison of uncorrected and bias corrected precipitation data with observed data, that the application of bias correction - although frequently criticized - is necessary to enable realistic simulations of discharge and soil erosion. Uncorrected data overestimate precipitation and result in wrong temporal pattern compared to observed data. Although the overestimation was reduced and the timing improved, bias correction was not able to completely remove the biases. Uncorrected temperature data of the six climate models fairly agree with observed temperature. But a uncorrected deviation of up to − 3 °C and the importance of temperature for the calculation of ETP motivated the bias correction of temperature.
2) All climate models except RCP4.5 of HIRHAM-EARTH predict an increase in uncorrected and bias corrected temperature between 0.9 °C and 2 °C. The future precipitation signal is not consistent. Some climate models (RACMO-EARTH, CCLM-CNRM, HIRHAM-NorESM) predict an increase, others a decreased or mixed signal (HIRHAM-EARTH, CCLM-ESM, CCLM-EARTH). Bias correction mostly did not alter the climate change signal of precipitation and if so (RCP4.5 of CCLM-ESM) it was attributed to a small climate change signal (0.01%) that was manipulated by the bias correction. The impact of climate change on return levels differs between models, return periods and emission scenarios. Most models predict small changes of return levels ranging from − 11% to + 21%. However, RCP4.5 of HIRHAM-EARTH and both RCPs of HIRHAM-NorESM show high increases in return levels which can be explained by improbably high precipitation rates which remain despite bias correction.

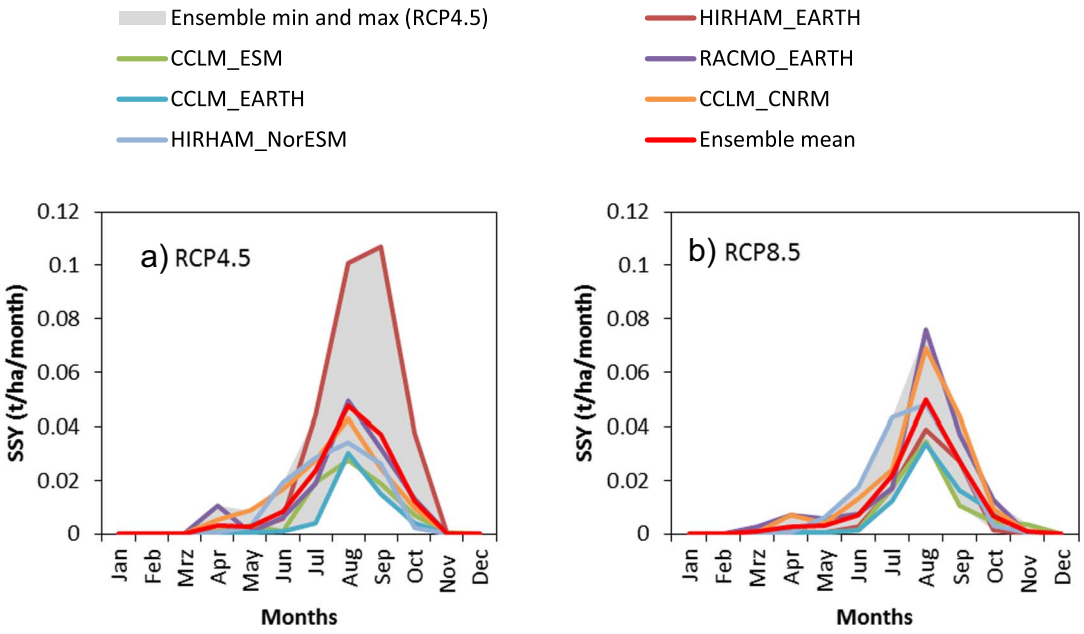

Fig. 11. Mean monthly specific suspended sediment yield (SSY) as simulated using bias corrected data from the climate model ensembles for RCP4.5 and RCP8.5 (2021–2050).

3) The comparison of simulated discharge and SSY derived from observed precipitation and temperature with simulated discharge and SSY derived from climate model data reveals that discharge and SSY simulated with input data from climate models is higher. This is attributed to an overestimation of modeled precipitation, which persists even after bias correction. However, the performance measures were good when bias corrected precipitation and temperature were used supporting the application of bias correction. Furthermore, the example of CCLM-ESM, which was run with and without bias corrected data, showed that neither the discharge nor the SSY signal were changed after bias correction. However, testing all climate models in the same way would be interesting but not possible due to the runtime of SHETRAN.
4) The impact of climate change on discharge and soil erosion was evaluated by comparing the historical period (1971–2000) with the future period (2021–2050). Three out of six climate models predict an increase of discharge and SSY (RACMO-EARTH, CCLM-CNRM, HIRHAM-NorESM) while the signals of two models are negative (CCLM-ESM, CCLM-EARTH). HIRHAM-EARTH predicts a mixed signal. The bias corrected precipitation signals are maintained by discharge and SSY. The ensemble mean suggests an increased discharge between 19.5% (RCP 8.5) and 36.5% (RCP 4.5) and an increased SSY of the same order. However, uncertainties resulting from the RCM-GCM outputs are large.

The bias correction, the model timestep, the model assumptions of SHETRAN and the measured precipitation data may play also an important role regarding the overall uncertainty but couldn't be explicitly addressed in the present work. In this context, we have to stress the large uncertainty of how the discharge in this catchment will develop by 2050. This is in agreement with other climate change studies in the region and has implications for possible climate change adaption strategies as potential discharge increase and decrease need to be considered.

This study supports the need for an improved climate observation network and climate projections for the region as they play a key role for the assessment of climate change impact on hydrology and soil erosion. Predicted soil erosion changes, ranging from − 45% up to + 217.3%, may strongly be increased or decreased if feedbacks between climate driven land cover changes as well as possible agricultural adaption strategies are included in a more complex model environment. Much progress has to be done, before reliable predictions of future soil erosion in West Africa are achieved.

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